CHAPTER 3

REVIEW OF LITERATURE

In the less developed countries of the world, breast cancer is a leading cause of cancer death. The World Health Organization in its press release[136] dated 12th December 2013, estimated the world breast cancer statistics in 2012, and stated that 1.7 million, i.e. 11.9% were diagnosed with breast cancer worldwide and there were 6.3 million women alive who had been diagnosed with breast cancer in the previous five years.

The overall classification and accuracy of digital mammograms in this thesis are based on dual tree M-band wavelet transform (DTMBWT) and Support Vector Machine (SVM). DTMBWT was initially proposed by Kingsbury [90] in 2001 and further investigated by Selesnick [106] in 2004 based on a Hilbert pair of wavelets for classifying mammogram and its subclasses. The results of screening the mammograms are organized into three stages. First stage (i) Classification of mammogram images either as normal or abnormal, (ii) If the abnormal image contained abnormality, they were further classified into masses and microcalcifications (iii) the given mass and microcalcifications image was further classified into benign or malignant.

The severity of the abnormality into benign or malignant either in mass or microcalcifications in mammograms through Computer Aided Diagnosis (CADx) is vital for the early diagnosis of the breast cancer.

Steffen et. al., [114] in 1993 constructed K-regular M-band orthonormal wavelet bases. In numerical analysis applications and in image coding using wavelet techniques, K regularity of the wavelet basis is known to be useful. M band wavelets were constructed from unitary filter banks which gave rise to wavelet tight frames in general (not orthonormal bases). Using two different approaches, an explicit formula for the magnitude-squared response of the unitary scaling filter that gave rise to minimal length K-regular M-band wavelets was also obtained.
Selesnick [106] in 2004 introduced the double-density dual-tree discrete wavelet transform (DWT), which was a DWT that combined the double-density DWT and the dual-tree DWT, each of which had its own characteristics and advantages.

Caroline Chaux et. al., [35] in 2004 concluded that dual-tree decompositions with more than two bands generally outperformed discrete orthonormal wavelet decompositions and dyadic dual tree representations.

In 2004, Caroline Chaux et. al., [34] showed that when the primal filter bank and its wavelets had symmetry, it was inherited by their duals.

Tony Lin et. al., [125] in 2005 proposed an algebraic approach to construct M-band orthonormal wavelet bases with perfect reconstruction.

Jun Wei et. al., [66] in 2005 developed a computer-aided detection (CAD) system for breast masses on full field digital mammographic (FFDM) images. The performance of the CAD system was evaluated using free-response receiver operating characteristic analysis. AD system achieved a case-based sensitivity of 70%, 80%, and 90% at 0.72, 1.08, and 1.82 false positive (FP) marks/image on the mass data set.

Bi Ning et. al. [12] in 2006 introduced a new family of multiband wavelets with a parameter for image coding. In multi band method of image coding, sub bands in the wavelet decomposition were adaptively divided into insignificant sub bands and significant sub bands while the latter further partitioned by a significance benchmark and by the quad-tree partition algorithm.

In 2009 Mohamed Meselhy et. al., [83] presented a new approach for breast cancer diagnosis in digital mammogram using curvelet transform

In 2010, Dheeba et. al., [44] proposed a new classification approach for detection of microcalcification clusters in digital mammograms. Microcalcification Cluster (MC) detection method was done in two stages. In the first stage, the original mammogram image was
decomposed using wavelet decomposition and gabor features were extracted from the original image Region of Interest (ROI). In the second stage, Back Propagation Neural Network (BPNN) was used for verifying the ability of the above features in detecting microcalcifications. Using the mammographic data from the Mammographic Image Analysis Society (MIAS) database a recognition score of 84.3% was achieved by the above approach.

In 2010, Bovis et. al., [14] designed a new approach where the texture features were calculated using histogram constructed from mammogram, which varied considerably, if the mammogram was over-enhanced or contained noise.


In 2011, Gensheng Zhang et. al., [59], in their review of breast tissue classification found that breast tissues presented in mammograms and breast cancer showed that radiologists could benefit from Computer-Aided Diagnosis (CAD) system with abilities of automated breast tissue classification. Recent breast tissue classification technologies compared three different types of approaches such as Texture feature analysis, Statistical Modeling, and Machine Learning. Texture feature analysis approaches are sensitive to different mammogram machines, and statistics modelling could be inaccurate in some specific situations.

In 2011, J.S.Leena Jasmine et. al., [76] developed an efficient automated mass classification system for breast cancer in digitized mammograms using Non Subsampled Contourlet Transform (NSCT) and Support Vector Machine (SVM).

Surendiran et. al., [119] in 2011 proposed the approach where the malignant and benign masses present in mammogram were classified using Hue, Saturation and Value (HSV) weight function based statistical measures.

In 2012, Pitchumani Angayarkanni et. al., [96] proposed for automatic segmentation of the mammogram images and classified them as benign, malignant or normal based on the
decision tree J48 algorithm and the size and the stages of the tumor were detected using the ellipsoid volume formula which was calculated over the segmented region.

In 2012 Don et. al., [49] proposed a new approach to classify mammogram images based on fractal features such as Fractal Dimension (FD) and Fractal Signature (FD).

Shanthi et. al., [107] in 2012, proposed a new approach for the classification of mammogram images using Self Adaptive Resource Allocation Network (SRAN). Intuitionistic Fuzzy C-Means Clustering (IFCM) technique was used to identify the suspicious region or the region of interest automatically.

In 2012, Belal K. Elfarra et. al., [9] proposed a new feature extraction method called Square Centroid Lines Gray Level Distribution Method (SCLGM) and used both Receiver Operating Characteristics (ROC) and confusing matrix to measure the performance.

A new approach DWT-DWT by Salim Lahmiri [101] [2012] for the detection of microcalcifications (MCs) in mammograms along with discrete Fourier Transform (FT) was proposed.

Mavudila et. al., [80] [2012] concluded that the implementation of M-band complex wavelet could be treated as the best for watermarking images in watermarking domain for medical images.

In 2012, Mohan Kumar et. al., [84] proposed the classification of microcalcification in digital mammogram by using Stochastic Neighbour Embedding (SNE) for reducing high dimensionality data into relatively low dimensional data and K-Nearest Neighbour (KNN) Classifier.

Subash Chandra Bose.J et. al., [116] (2012) proposed a new method for the detection and classifications of micro calcifications using soft computing techniques consisting of four stages, namely preprocessing, segmentation, feature extraction and classification using Fuzzy c-Means clustering (FCM) Fuzzy C-Means Clustering (FCM) for segmentation and pectoral muscle extraction, and two dimensional discrete wavelet transforms and Artificial Neural Network.
Leena Jasmine et. al., [75] in 2012 presented a method for the classification of microcalcification in digital mammograms using Non Subsampled Contourlet Transform (NSCT) and Support Vector Machine (SVM). The system classified the mammogram images as normal or abnormal, and the abnormal severity as benign or malignant with improved classification rate of over 90% for all cases.

Ayman AbuBaker [6] (2012) presented a novel method for the detection of the mass lesions in the mammogram images using three main stages, detection region of interest, extraction wavelet features using Discrete Wavelet Transform (DWT) and Support Vector Machines (SVM) with the ANOVA kernel for reducing the number of the FP regions in the mammogram images.

Eden.A et. al., [53] in 2012 presented a CAD model based on computer vision procedures for locating suspicious regions that were later analyzed by artificial neural networks, support vector machines and linear discriminant analysis, to classify them into benign or malignant, based on a set of features that were extracted from lesions to characterize their visual content.

Nasseer M. Basheer et. al., [89] 2013, proposed Computer Aided Diagnosis (CADx) systems for classifying abnormal masses in digital mammograms using Support Vector Machines (SVM).

Bhanumathi et. al., [10] (2013) presented an overview of the recent advances in the development of CAD systems and related techniques described some fundamental concepts related to breast cancer detection and reviewed many key CAD techniques for breast cancer including detection of masses, calcification, architectural distortion, bilateral asymmetry in mammograms.

Mussarat Yasmin et. al., [86] in (2013) presented a survey paper and overviewed the techniques and algorithms proposed for the detection of breast tumor and for interpreting its stage in some cases so that proper treatment could be given to the cancer patient for improving her life quality. The study attempted to highlight the available breast cancer detection techniques
based on image processing and provided an overview about the affordability, reliability and outcomes of each technique.

In 2013, Ramani et. al., [99] concluded the adaptive median filter was a more appropriate method compared with the other filters, namely average filter, adaptive median filter, average or mean filter and wiener filter because image quality of adaptive median filter was better than the others.

In 2013, Nabiha Azizi et. al., [88] proposed and evaluated a new system for the detection of breast masses that was based on classifier fusion with features cooperation. They investigated a computer-aided diagnosis system for breast cancer by developing a novel classifier fusion scheme based on the fusion of three support vector machine classifiers.

In 2013, Caroline Chaux et. al. [33] proposed an extension of the work by I. Selesnick[112] on Hilbert transform pairs of wavelet bases to the orthogonal M-band case, by establishing phase conditions on the related filters.

Srishti Sondele and Indu Saini [113] (2013) presented a feature extraction technique i.e., Bidimensional Empirical Mode Decomposition (BEMD) for mammogram feature extraction. Features of mammogram images were extracted using BEMD and mammograms were classified as normal, masses and calcification, using ANN pattern recognition method and good accuracy was obtained by using BEMD features with ANN.

In the year [2013], Anuradha C.Phadke and et. al., [4] developed a CAD system to classify Architectural Distortion abnormality from the other malignant abnormalities and normal mammogram samples. To detect architectural distortion, Gabor features and Law’s Texture Energy measures were used. Support Vector Machine (SVM) was used for the classification. They concluded that their algorithm could not differentiate well between architectural distortion and speculated lesions and hence in order to differentiate between these two types of abnormalities additional features needed to be explored.

In 2013, Kumar et al. [72] presented a digital mammogram based on Discrete Wavelet Transform (DWT) and Stochastic Neighbor Embedding (SNE) technique. In this proposed system KNN and SVM classifiers were used to classify the mammograms.

Herwanto et al. [64] in 2013 proposed a method that could be used for a specific application in the detection of microcalcification and mass in mammogram using a new method with statistical features of mean and Gray Level Co-occurrence Matrix (GLCM) homogeneity.

In 2013, Banumathi et al. [11] proposed a Support Vector Machine (SVM) based classifier to detect the microcalcification at each location in the mammogram.

Kohei Arai et al. [70] in 2013 presented a classification system with Daubechies D4 wavelet for feature extraction and support vector machine (SVM) classifier for effective binary classification.

Daniel Rodrigues Ericeira et al. [42] [2013] proposed a methodology for detecting masses by determining certain asymmetric regions between the pairs of the mammograms of the left and the right breasts using a spatial descriptor called cross-variogram function and Support Vector Machine (SVM).

In, 2014, Kaushik Sinha et al. [67] proposed a study on the different techniques of noise removal from an image using M-Band Wavelet Transform.

Suman Mishra et al. [118] (2014) proposed a novel multilayer architecture for the classification of digital mammogram based on dyadic wavelet transformation and Gaussian Mixture Model (GMM).

In 2014, C. Rekha et al. [100] [2014] investigated a classification of mammogram using GLCM texture feature and Artificial Neural Network (ANN).
Komal Chaudhari et. al., [71] [2014] presented various techniques used for automatic enhancement and segmentation of microcalcifications in mammographic images and proposed a system in which the stages (preprocessing stage, feature extraction stage, and classification stage) could be implemented using histogram equalization, contrast stretching, image segmentation and nonsubsampled contourlet transform.

Mohan Kumar et. al., [51] [2015] presented the performance evaluation of the computer aided diagnostic system for the classification of mass classification in digital mammogram based on Discrete Wavelet Transform (DWT), Stochastic Neighbor Embedding (SNE) and the Support Vector Machine (SVM). The maximum accuracy obtained by SNE was decomposition at all levels and applied on the wavelet sub-bands individually.